# IMPLEMENTATION STRATEGY FOR SMART MAINTENANCE MANAGEMENT SYSTEM

**A SYNOPSIS**

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## 1. INTRODUCTION

Starting from the first Industrial Revolution in 18th Century to the fourth Industrial Revolution (Industry 4.0), the manufacturing segment of the world has undergone successive transformation for meeting out the ever-increasing requirements in terms of mass production, product quality, productivity, reaping the capability of the technological advancements such as ICT, Cloud Computing, Machine Learning, Artificial Intelligence, Internet of Things, Data Mining and so on. Primary objective of every transformation has been to improve the overall performance/productivity, product quality and customer satisfaction, which in turn necessitate continuous improvement in plant availability and improved upkeeping of all production facilities. Hence, throughout the different phases of industrial revolution the maintenance function has also undergone successive transformations from break down maintenance to preventive maintenance to conditioning monitoring and so on.

With the advent of the industry 4.0 and Industrial Internet of Things (IIoT) the real-time capturing of the data and data analysis has made it possible to continuously monitor the health (condition) of the all the production and service facilities of a production shop and maintaining the values of the maintenance parameters such as failure rate, service rate, and the like, and continuously improving upon them. This has resulted the hope of increasing the remaining useful lifetime of individual machines, more particularly the critical bottleneck facilities which decide the plant availability/capacity.

In this research work, an effort has been made to formulate a framework of Smart Maintenance Management System comprising a prognostic health management system (catering to all production facilities), which utilizes the real-time captured data from the individual machines, comparing with it desired range of values for the respective data, communicating to the maintenance crew, in case of any deviation, for initiating preventive actions and recording the live data for the further analysis and use.

## 2. LITERATURE REVIEW

The smart maintenance management system coupled with the mathematical modelling, analysis, optimization, and real-time health monitoring process by the application of the recent technologies such as IIoT, ICT, Could Computing and Data analysis is an emerging filed in the recent revolution of industry (Industry 4.0). The selective literatures related to this field, discussed in the thesis are highlighted here as below:

Vikrant and Atul [1] described the papermaking system's Maintenance Management functions. Markov Analysis is used to assess the condition and availability of a critical subsystem, and the result is the deployment of a critical subsystem availability and predictive maintenance system in the papermaking system.

Kumar et al. [2], Aggarwal et al. [3], Kadiyan et al. [4] and Khanduja et al. [5]. discussed the performance modelling and availability/reliability analysis of the different systems in various manufacturing plants in greater depth. Using the Transition Diagram of the manufacturing system, the Markov model, first-order Chapman–Kolmogorov differential equations, and the Range Kutta fourth-order method, they have developed suitable maintenance techniques for increasing the performance of the subsystem availability in the production plant.

Chawla and Kumar [6] discussed the Condition Based Maintenance Model of repairable machine components in depth, in order to maximise the availability of a given repairable system. With the use of MATLAB software, they solved the mathematical equation using the Range Kutta method, and the Markov Model. based on that, predicted/condition-based optimal maintenance strategy for repairable components, has been formulated.

Gupta [7] examined the performance analysis of a coal-based thermal power plant's water condensate system in northern India and Sharma and Kumar [8] analysed the paper making production system. They used the traditional Markov model approach and Chapman–Kolmogorov equations developed from the subsystem's transition diagram to analyse one of those subsystems in the thermal power plant, paper making

production plant and suggested a suitable technique for stochastic modelling and availability evaluation of the given subsystem.

Li et al. [9] explained the various models in the data mining process in the implementation of the predictive maintenance management system in a machining center. They collected the data from the machining centre for the predictive maintenance activity by the application of the Data Mining and Artificial Neural Network approach. The Artificial Neural Network was applied for fault detection purposes, and data mining was applied to the predictive maintenance management systems in the machining centres of the manufacturing industry.

Patel and Patel [10] discussed the factors and challenges of implementing the next industrial revolution with new technology in greater depth. They considered the Internet of Things' framework and architecture, as well as Cyber-Physical Systems for the creation of smart daily life functions and the smart factory for the next industrial revolution.

Kuo et al. [11] discussed in detail the implementation of the Industry 4.0 concept in small and medium-sized industries. They analysed the spring manufacturing industry to produce smart manufacturing systems and predict the machine status for next production by the application of the Internet of Things, information and communication technology, and artificial neural networks in the spring production unit of the manufacturing industry.

Li et al. [12] discussed potential predictive maintenance policy in the fourth revolution of industry (Industry 4.0) application of some new technologies: Internet of Things, Internet of Service, Cyber-Physical Systems, and Cloud Computing. They developed an optimal and autonomous maintenance management system in industry 4.0.

Chiu et al. [13] explained in detail the predictive maintenance policy of the solar cell factory. They described an existing maintenance system and developed the new maintenance policy for the next revolution of the industry through the application of the Health Index Hierarchy analysis, Intelligence Preventive Maintenance techniques, Cloud Computing, Internet of Things, and Cypher Physical Systems in the maintenance management systems.

Schmidt and Wang [14] examined the Predictive Maintenance approach for the machine tool life cycle in the manufacturing industry by the application of the recent techniques such as Machine Learning Algorithm, Continuous Monitoring Maintenance, Condition Based Maintenance, Cloud Computing, Big Data Analysis, Internet of Things and Analysis techniques. The Mante–Carlo Analysis, Principal Component Analysis, Weibull Cumulative Distribution were used to organise the autonomous maintenance management activity in the manufacturing industry.

De Saporta and Zhang [15] used the Piecewise-Deterministic Markov process to predict the failure or fault in the heated hold-up tank before it occurs, provided the optimal maintenance activity, and organised the maintenance department's predictive maintenance management system.

In the manufacturing industry, Van Horenbeek and Pintelon [16] justified and developed the Predictive Maintenance strategy of a complicated multi-component systems to reduce the long-term maintenance cost per unit time of machine components in that industry.

Masoni et al. [17] examined remote maintenance in industry 4.0 through the application of the Augmented Reality Technology. This technology makes it easy to communicate and connect with unskilled labour and skilled trainers from the operating control room to the working environment of the industry. They also used this technology to organize remote maintenance and to guide unskilled labour in resolving the problem through 3D image representation, Demo Videos, and text chat.

Dong et al. [18] detailed discussed the Internet of Things application in the coal mining industry. By applying this technology, they achieved continuous health monitoring of the coal mining equipment, especially in ventilator equipment, to produce safety and predictive maintenance activity.

Voisin et al. [19] explained the CNC Machine Tool Health Monitoring systems in the German automobile manufacturing industry. They analysed the machining tool's remaining useful life with the Prognostic Health Monitoring System, then developed the new framework of Predictive Maintenance policy and monitored the quality deviation of the CNC machine tool by the application techniques such as Structured Analysis and Design Technique, Failure Mode Effective Analysis, Hazard and Operability Study, and Static Process Control.

Ruschel et al. [20] explained the maintenance planning of process shop floor having CNC machines. They developed and produced optimal maintenance scheduling and reduced maintenance activity downtime in the shop floor by using forecasting analysis methods such as the Bayesian Network model and Fuzzy Interference Algorithm.

## 3. RESEARCH GAP

From the literature survey conducted, it is found that production system with occurrence of independent failures of machines only so far have been studied for modelling and analysis, whereas in all the production system in practice invariably have simultaneous failure of machines. Hence, in this research, the maidan effort of modelling of simultaneous failures is taken. Also, so far optimization of parameter values for the individual machine only has been done in the past, whereas in this work, not only, for the production system as whole is taken for the research, but also, the framework to continuously monitor the maintenance parameter and initiating predictive maintenance (in case of deviation from the desired/optimal value) actions has been attempted to.

## 4. OBJECTIVES

The objectives of this research work are

(i) To develop a mathematical model to represent the complex interconnectivity of the production facilities each having different maintenance parameters

(ii) To do mathematical analysis to identify critical/bottle-neck facilities that affect the overall performance of the system so that focus can be made on a priority basis.

(iii) To arrive at optimal/nearer-to-optimal values of the maintenance parameters to the individual facilities to achieve the maximum possible performance of the production system.

(iv) To develop a framework of a smart maintenance system with a health prognostic system to continuously monitor the individual facilities for any deviation from the standard/desired value.

(v) To formulate an implementation strategy by involving all stakeholders, developing a prototype, and testing in a laboratory and implementing in one or two case study production unit.

## 5. RESEARCH PROBLEM STATEMENT

To maximize the overall performance of modern production systems which comprise of complex network of interconnected production and service facilities each having different and independent maintenance characteristics such as failure rate, service rate and the like. The performance of any such production system, which is normally engaged in different varieties and volume of products largely depends on how well the system component-facilities are maintained, and hence the availability/capacity of the entire system is made at its possible maximum, which can be achieved through establishing an intelligent and smart maintenance system. Hence it is imperative to model the complex production system to understand the inter relationship among the facilities, do mathematical analysis on their dynamic behaviors, predict the availability with respect to different values of the maintenance parameters. Through the analysis optimal values of the maintenance parameters can be fixed for the desired level of performance of production system. With the capabilities of the latest technologies described in the previous section, a continuous health prognostic system must be developed to ensure that each constituent facilities of the system is continuously monitored, their real-time failure rate and service rate are evaluated by capturing the live-data and comparing it with the desired (optimal) range of data. In case of any deviation, the autonomous heath prognostic system should instantaneously send alarming message(s) to the maintenance staff to initiate appropriate preventive/corrective measures to remove the deviations and to continuously maintain and improve the health of the facilities and the overall performance of the production system.

## 6. METHODOLOGY

In this research, a methodology using Markovian Decision Model is developed to measure the performance of an existing maintenance system, in terms of maintenance indices like Reliability, Availability, MTTF, MTTR, Dependability and so on and

thereby to fix the critical machines in the system. The model is developed to cater to both (1) Simple production system with occurrence of independent failures of machines and (2) Complex production system with occurrence of independent as well as simultaneous failure of machines, are studied to fix the critical machines

The model is tested with two different case study production systems (viz, a tyre manufacturing plant and an automobile spare parts manufacturing shop) exhibiting the above- mentioned two different failure characteristics. Markov Birth-Death process model widely used to measure the maintenance parameters **R**eliability-**A**vailability-**M**aintainability-**D**ependability (**RAMD**) of any production system with facilities that can be seen in any one of three different state/condition viz., (i) Working state, (ii) Under-maintenance state and (iii) Failed state, is adapted in this work. The interrelationship among the subsystems is modelled by using the transition state diagrams as shown in Figure.1 The notations used in the mathematical model developed are as under

$S_i$ - Working state of the subsystem *i*

$\underline{S}_i$ - Under-maintenance state of the subsystem *i*

$*S_i$ - Repair state of the subsystem *i*

$\lambda_i$ - Failure rate of the subsystem *i*

$\mu_i$ - Repair rate of the subsystem *i*

$\phi_i$ - Transition rate of the subsystem *i*

$\eta_i$ - PM rate of the subsystems *i*

where $i \subset$ {BM, BB, CL, BC, EX, BD, CU}

(BM - Banbury Mixing subsystem, BB - Bead and Belt cord manufacturing subsystem, CL - Calendaring Subsystem, BC - Bias Cutting subsystem, EX - Extruding subsystem, BD - Building subsystem, CU - Curing subsystem)

b - Constant (0 for ideal and 1 for faulty)

$P_0(t)$ - Probability function for subsystem being in working state

$P_1(t)$ - Probability functions for subsystem being in under-maintenance state

$P_2(t)$ - Probability function for subsystem being in repair state

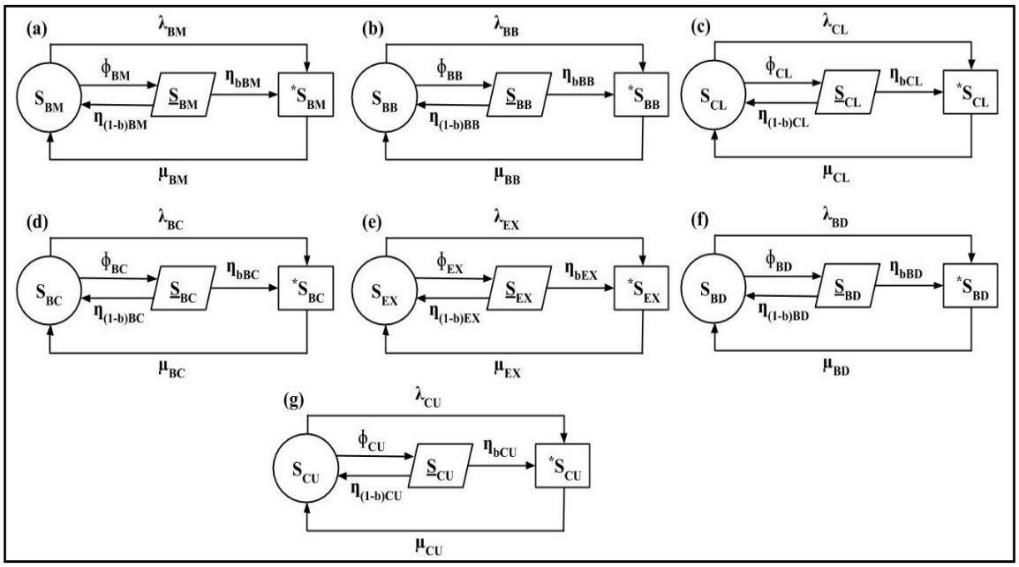


**Figure 1.** Transition State Diagram of Tyre Manufacturing System

The mathematical equations derived (using the Markovian Process) to express the recurrence relationship of subsystems is as below.

$$P'_0(t) = \eta_{i(1-b)}P_0(t) + \mu_i P_2(t) - \phi_i P_0(t) - \lambda_i P_0(t) \quad (1)$$

$$P'_1(t) = \phi_i P_0(t) - \eta_{i(1-b)}P_1(t) - \eta_{ib}P_1(t) \quad (2)$$

$$P'_2(t) = \eta_{ib}P_1(t) + \lambda_i P_0(t) - \mu_i P_2(t) \quad (3)$$

At initial state (at time t = 0) equations (1) to (3) converges to,

$$\eta_{i(1-b)}P_0 + \mu_i P_2 - \phi_i P_0 - \lambda_i P_0 = 0 \quad (4)$$

$$\phi_i P_0 - \eta_{i(1-b)}P_1 - \eta_{ib}P_1 = 0 \quad (5)$$

$$\eta_{ib}P_1 + \lambda_i P_0 - \mu_i P_2 = 0 \quad (6)$$

On solving these three equations for $P_0$, $P_1$ and $P_2$, and on applying the normalized state conditions on equations 4-6 the availability of sub system for time *t* is derived, as shown in Equation 8

$$\sum_{j}^{n} Pj = 1 \Rightarrow P_0 + P_1 + P_2 = 1 \quad (7)$$

where $j$ = 0, 1 and 2

$$AV_i = \left[1 + \left(\frac{\phi_i}{\eta_{i(1-b)} + \eta_{ib}}\right) + \left(\frac{\phi_i \times \eta_{ib} + \lambda_i}{\mu_i(\eta_{i(1-b)} + \eta_{ib})}\right)\right]^{-1} \quad (8)$$

Using the discrete stochastic mathematical model, by analyzing the present state and behavior ($\lambda_i$ , $\mu_i$ , $\phi_i$, $\Pi_i$ ) of the system the future state (RAMD) of the system is predicted by solving the above three equations. The real-time data from the records of the maintenance department of the plant ($\lambda_i$ , $\mu_i$ , $\phi_i$, $\Pi_i$ ) are taken as input for the RAMD analysis.

From the output of the analysis, shown in Table 1, the most critical machine BC (with minimum R, minimum Av and the like) is identified. As the plant availability largely depends on the maintenance parameters such as the failure rate (λ), service rate (μ), transition rate (ϕ) and preventive maintenance rate (η), it is essential to find the optimal or near-optimal values of these maintenance parameters for the individual machines, so that the desired maximum availability of the entire production plant can be achieved.

**Table 1.** RAMD indices of the production system

| **RAMD indices** | **SBM** | **SBB** | **SCL** | **SBC** | **SEX** | **SBD** | **SCU** |
|---|---|---|---|---|---|---|---|
| Reliability | $e^{-0.008t}$ | $e^{-0.007t}$ | $e^{-0.004t}$ | $e^{-0.005t}$ | $e^{-0.007t}$ | $e^{-0.003t}$ | $e^{-0.002t}$ |
| Maintainability | $1- e^{-.150t}$ | $1- e^{-.138t}$ | $1- e^{-.290t}$ | $1- e^{-.158t}$ | $1- e^{-.144t}$ | $1- e^{-.244t}$ | $1- e^{-.310t}$ |
| Availability (Faulty) | 0.8827 | 0.8859 | 0.9344 | 0.8387 | 0.8555 | 0.9339 | 0.9535 |
| Availability (Ideal) | 0.9206 | 0.9153 | 0.9528 | 0.8523 | 0.8982 | 0.9485 | 0.9594 |
| Dependability | 7.52 | 7.76 | 14.24 | 5.19 | 5.92 | 14.12 | 20.5 |
| MTTR (Faulty) | 16.61h | 18.28h | 17.55h | 38.46h | 23.98h | 23.59h | 24.38h |
| MTTR (Ideal) | 10.78h | 13.21h | 12.38h | 29.34h | 16.09h | 18.09h | 21.15h |
| MTBF | 125.0h | 142.8h | 250.0h | 200.0h | 142.0h | 333.3h | 500.0h |
| Dep. Ratio ($D_{Min}$) | 0.9025 | 0.9049 | 0.9429 | 0.8701 | 0.8823 | 0.9422 | 0.9582 |

In this research work, a Genetic Algorithm (GA) based methodology, to fix the optimal values of the maintenance parameters for the individual machines is developed. GA based framework is shown in Figure 2. below;

**Step 1:** Initialize the parameters (λ, μ, ϕ and η) and code the solution strings

**Step 2:** Randomly generate the initial population

**Step 3:** Compute the fitness function (Av) for solutions in the population

**Step 4:** Create mating pool from the population as per cross over probability

**Step 5:** Select two parents from the mating pool at random.

**Step 6:** Perform the crossover of the parents to produce the two offspring.

**Step 7:** Mutate as per mutation probability

**Step 8:** Place the child strings to new populations

**Step 9:** Compute the fitness value, Av of individuals in the resultant population.

**Step 10:** Generate the new population using the selection operator

**Step 11:** Repeat the step 4 to step 10 until the termination criterion is met

**Step 12:** Select the best solution with maximum Av from the final population

**Figure 2.** GA based Optimization Methodology

Method of implementing the methodology is explained in detail in the thesis, with respect to another case study production plant, *Cross member production plant* represented by the state transition diagram as shown in Figure. 3

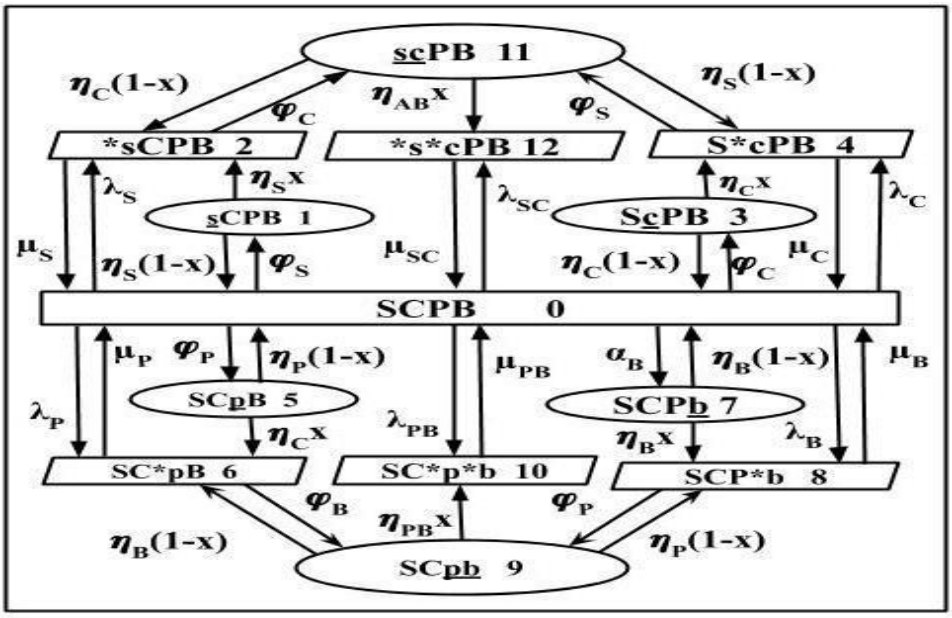


**Figure 3.** Transition State Diagram of the *Cross-member* Production System

The optimal values of the maintenance parameters for each facility of the production system (S,C,P,B), at the end of GA termination is shown in the Table 2.

**Table 2.** Optimal Maintenance Parameters of the Production System

| b | Av | Optimal values of maintenance parameters | Av | Optimal values of maintenance parameters |
|---|---|---|---|---|
| 1 | 69.80% | $\lambda_S$=0.0336,$\lambda_C$=0.0286, $\lambda_P$=0.0456, $\lambda_B$=0.0479, $\lambda_{SC}$=0.0425,$\lambda_{PB}$=0.037, $\mu_S$=0.9705,$\mu_C$=1.0094, $\mu_P$=1.2533, $\mu_B$=0.9903, $\mu_{SC}$=1.0027, $\mu_{PB}$=0.8049, $\phi_S$=0.0452,$\phi_C$=0.0030, $\phi_P$=0.0387, $\phi_B$=0.0058, $\phi_{SC}$=0.0196, $\phi_{PB}$=0.0207, $\eta_S$= 0.8310, $\eta_C$=0.9808, $\eta_P$=1.1803, $\eta_B$=0.5425, $\eta_{SC}$= 0.7818, $\eta_{PB}$=0.7838. | 73.25% | $\lambda_S$=0.0477, $\lambda_C$=0.0249, $\lambda_P$=0.0509, $\lambda_B$=0.0344, $\lambda_{SC}$=0.0454, $\lambda_{PB}$=0.0561, $\mu_S$=0.7789, $\mu_C$=1.1043, $\mu_P$=0.8739, $\mu_B$=0.8416, $\mu_{SC}$=1.0565, $\mu_{PB}$=1.0817, $\phi_S$=0.0311, $\phi_C$=0.0050, $\phi_P$=0.0102, $\phi_B$=0.0041, $\phi_{SC}$=0.0415, $\phi_{PB}$=0.0273, $\eta_S$=0.8291, $\eta_C$=1.0189, $\eta_P$=0.4048, $\eta_B$=0.6716, $\eta_{SC}$=0.5735,$\eta_{PB}$=0.9226 |
| 0 | 76.17% | $\lambda_S$=0.0396, $\lambda_C$=0.0230, $\lambda_P$=0.476, $\lambda_B$=0.0465, $\lambda_{SC}$=0.0251, $\lambda_{PB}$=0.0277, $\mu_S$=0.8483, $\mu_C$=0.7551, $\mu_P$=0.6910, $\mu_B$=1.0216, $\mu_{SC}$=1.1191, $\mu_{PB}$=0.9066, $\phi_S$=0.00137, $\phi_C$=0.0088, $\phi_P$=0.0131, $\phi_B$=0.0104, $\phi_{SC}$=0.0121, $\phi_{PB}$=0.0202, $\eta_S$=0.4075, $\eta_C$=0.8761, $\eta_P$=1.1901, $\eta_B$=0.9024, $\eta_{SC}$=0.6615, $\eta_{PB}$=0.3261. | 75.58% | $\lambda_S$=0.0387, $\lambda_C$=0.0345, $\lambda_P$=0.0360, $\lambda_B$=0.0261, $\lambda_{SC}$=0.0496, $\lambda_{PB}$=0.0411, $\mu_S$=1.0635, $\mu_C$=0.9194, $\mu_P$=0.9942, $\mu_B$=0.8817, $\mu_{SC}$=0.9939, $\mu_{PB}$=1.0905, $\phi_S$=0.0255, $\phi_C$=0.0016, $\phi_P$=0.0423, $\phi_B$=0.0173, $\phi_{SC}$=0.0110, $\phi_{PB}$=0.0384, $\eta_S$=0.7870, $\eta_C$=0.6189, $\eta_P$=1.0180, $\eta_B$=1.0481, $\eta_{SC}$=0.7691, $\eta_{PB}$=1.1779 |

In this work, primary focus is made on the maintenance and service management system of a typical smart factory supported with optimal decision-making process. The industrial rotary systems are the most significant components in the

manufacturing systems in any industry. Hence, in this work, industrial hydraulic pump has been investigated to develop a new smart maintenance and service framework with the optimal decision-making process

In this work, a real-time, continuous health monitoring system of the rotary systems has been implemented as per the requirement of the autonomous (smart) maintenance management, in the smart factory systems, to ensure that the operating parameters of the rotary system are maintained within the acceptable/optimal range and thereby maximizing the uptime of the production line. The proposed smart maintenance management system involving a continuous health monitoring and prognostic framework, designed for the critical component, the rotary system of the manufacturing process of SMEs is shown in Figure 4. The logical flow chart of the decision support system built into smart maintenance management system, is shown in the Figure 5.

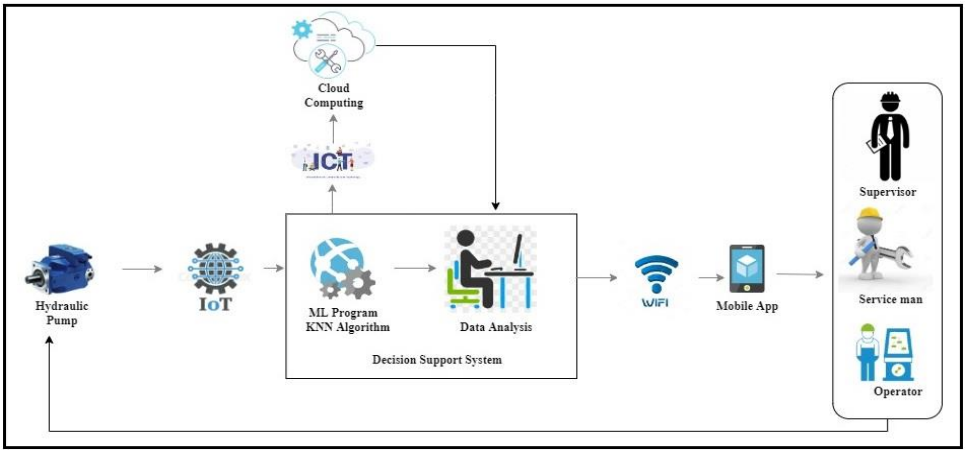


**Figure 4.** Architecture of the Prognostic Health Management System

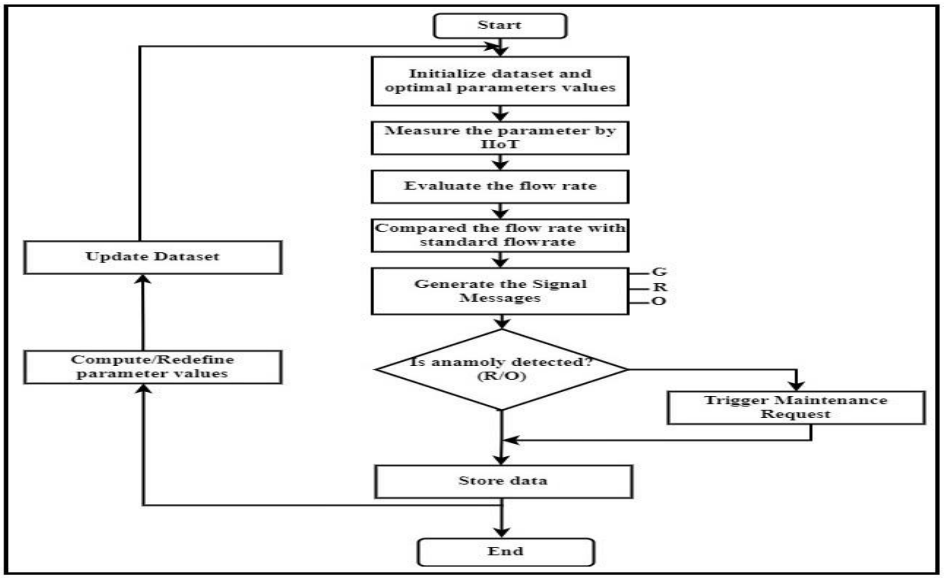


**Figure 5.** Decision Support System of Smart Maintenance Management

Before implementing the developed system in the actual production line, it was tested by building a protype in the laboratory with similar set-up. On successful trials with the protype, the developed continuous prognostic health management system was implemented in a heavy-duty gear pump, a critical facility in a case study production plant producing sensors and switches for automobiles, with an objective of establishing a smart maintenance management system under a typical Industry 4.0 environment. The performance of pump in terms of the maintenance metric like average number of failures, average downtime, average service manhours are measured after implementing the proposed system and it is found to be much better compared to the performance before implementation. Also, the performance is observed to be progressively improving with passage of time.

## 7. ORGANISATION OF THESIS

The organization of the thesis is as below:

**Chapter 1:** The initial chapter is introductory and provides the summary of the background of this thesis. The chapter contains the research problem statements, objectives and quintessence of the research work, done.

**Chapter 2:** In this chapter, a detailed survey about the maintenance functions of production enterprises, modelling and analysis of maintenance problems, Industry 4.0 and related technologies related to autonomous maintenance systems and the research gap and prospective is identified.

**Chapter 3:** In this chapter, the methodology to model the maintenance system of a complex production system is developed using Markovian birth-death process and through RAMD analysis, to identify bottleneck facilities.

**Chapter 4:** In this chapter a GA based optimization procedure to search for the desired/optimal values for the maintenance parameters of subsystems of a production system with the objective of maximizing the overall performance of the production system.

**Chapter 5:** This chapter describes the framework developed for a smart maintenance system and strategy to implement the framework by designing and implementing a continuous prognostic health management system.

**Chapter 6:** This chapter presents the summary of the research findings, conclusions, and scope for future research work.

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## 9. LIST OF PUBLICATIONS


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